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Medical Image Registration Based Retrieval

Swarnambiga AYYACHAMY[1,*] and Vasuki MANNIVANNAN[2]

[1] SACS MAVMM Engineering College, Madurai - 625 301, Tamil Nadu, India.
[2] Velammal College of Engineering &Technology, Viraganoor, Madurai-09, India.
E-mail: aswarnambiga@gmail.com, hello_vasuki@yahoo.co.in

* Author to whom correspondence should be addressed; Tel.: 0452-4522522098.

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Abstract
This paper presents a quantitative evaluation of state-of-the art intensity based image registration with retrieval methods applied to medical images. The purpose of this study is to access the stability of these methods for medical image analysis. The accuracy of this medical image retrieval with affine based registration and without registration is evaluated using observer study. For retrieval without registration and with registration, we examine the performance of various transform methods for the retrieval of medical images by extracting the features. This helps for the early diagnosis. The technique used for retrieval of medical images were a set of 2-D discrete Fourier transform (DFT), discrete cosine transform (DCT), discrete wavelet transform (DWT), Complex wavelet transform (CWT), and rotated complex wavelet filters (RCWF) were implemented and examined for MRI imaging modalities. Especially RCWF gives texture information strongly oriented in six different directions (45° apart from the complex wavelet transform). Experimental results indicate that the DWT method perform well in retrieval of medical images. The method also retains the comparable levels of computational complexity. Then the experimental evaluation is carried by calculating the precision and recall values. It is found that DWT performs well for retrieval without registration and CWT with affine performs well in registration based retrieval with efficiency of 92% from retrieval efficiency 83% of DWT without registration. This helps in classification as before registration and after registration especially for clinical treatment and diagnosis.

Keywords: Registration; Retrieval; Content based image retrieval; Texture based medical image retrieval; Transforms.

Introduction

Medical imaging technologies are altering the nature of many medical professions today. The purpose of this article is twofold. First, we experiment some of the most promising retrieval and registration strategies currently used in medical imaging. We show that all these techniques may be phrased in terms of a variation problem and allow for a unified treatment. Second, we introduce, with the new framework, a new registration based retrieval on medical images. We show variations with affine linear transformation based retrieval and without. Furthermore, we develop a stable and fast implementation of the new scheme based on transforms. We demonstrate the advantages of the new technique for data sets and present an application of the algorithm for registering and retrieval of medical images. The observation from the experimentation is registration based retrieval also performs well in retrieval process. The problem so far faced were application of registration and retrieval in clinical diagnosis and suggestion were performed separately, but ,now here we have experimented registration, retrieval and registration based retrieval separately for medical images and evaluated their performance. The main contribution from this work is medical image registration based retrieval.

Aim

Medical imaging techniques were used to evaluate an area of body that is not extremely visible. Medical diagnosis is process of identifying by symptoms and results from medical imaging. Medical images were increasingly being used within healthcare and diagnosis, surgical planning, treatment and monitoring disease progression. Multiple images were acquired from subjects at different times, and often with different imaging modalities. The imaging modalities were divided in to two global categories: Anatomical and Functional imaging modalities. Anatomical modalities, i.e. depicting primarily the morphology, include X-RAY, CT (Computed Tomography), MRI (Magnetic Resonance Imaging), US (Ultra Sound).

Earlier methods suffer from two main drawbacks. They are,

- Computationally expensive.
- Retrieval accuracy is poor.

In this article we concentrate on the problem of finding good texture features for medical images reducing the computational complexities, computational expensiveness and increasing the retrieval accuracy. The main approach followed here is affine based image registration which is applied for retrieval of medical images.

The main contribution and nature of this article are summarized as follows,

- Implementation of registration based retrieval, which yields retrieval results with better accuracy.
- Formulation of new results using the proposed approach.

Material and Method

Material

Affine based registration is performed for medical images. To improve the retrieval performance both in terms of retrieval accuracy and time for medical images, in this paper, we have introduced a joint approach for registration based retrieval. In this paper, we aim to provide a more thorough insight on the use of intensity – based affine registration algorithms applied to brain images. The above mentioned is our first approach and results are evaluated separately. The second approach is to calculate the retrieval performance in terms of retrieval accuracy, for that a set of transforms were experimented. A detailed comparison with the performance of transforms using texture features is provided. Earlier methods for transform based image retrieval focus on anyone of the transforms up to our knowledge. In this article, we concentrate on 2-D discrete Fourier transform (DFT), discrete cosine transform (DCT), discrete wavelet transforms (DWT), complex wavelet transforms (CWT), rotated complex wavelet transform filter (RCWF), for efficient retrieval both in terms of accuracy and computational complexity. After separately performing the registration and retrieval a combined approach of registration based retrieval is performed. Then affine based registered images based registered images were applied in the retrieval. Both registration and retrieval were carried by using a same database. Then we evaluate the performance of retrieval before and after registration. Our approach has two fold advantages over other approaches. First, the retrieval accuracy for before and after registration is experimented in a singer take over. Additionally, the retrieval performance of joint method outperforms other registration based retrieval methods. The rest of the paper is organized as follows. The medical image registration is organized in section 2. In Section 3, medical image retrieval is briefly discussed. An implementation of medical image registration and medical image retrieval is given in section 4. Experiments and discussion were given is section 5. Finally discussion is followed with conclusion.

Methods

Affine based registration is performed for medical images. To improve the retrieval performance both in terms of retrieval accuracy and time for medical images, in this paper, we have introduced a joint approach for registration based retrieval. In this paper, we aim to provide a more thorough insight on the use of intensity - based affine registration algorithms applied to brain images. The above mentioned is our first approach and results are evaluated separately. The second approach is to calculate the retrieval performance in terms of retrieval accuracy, for that a set of transforms were experimented. A detailed comparison with the performance of transforms using texture features is provided. Earlier methods for transform

Medical Image Registration

The main goal of this work is to review and evaluate the applicability of one-state-of-the art intensity based image registration algorithm to brain images, more specifically to temporal studies: two images of the same brain acquired at different time intervals, normally different screening rounds which were taken at 1-2 years apart. Totally, our data comprise 1000 digitized brain images from 10 patients in Sagittal, Coronal and Temporal views. Initial results with a more extensive evaluation and discussion are addressed here [2-4]. An affine based medical image registration was applied to all medical imaging modalities. A detailed evaluation for MRI images registration is done here.

A. Global Transformations (Affine)

We refer to global methods as the ones in which all pixels suffer the same transformation, which often results in simple and fast computation due to its small number of parameters. Rigid and affine transformations are proposed as global transformations. It is a combination of several simple special mappings, such as the identity, translation, scaling, rotation, reflection and shear [1]. An affine transformation $t = \{[A], b\}$ in 2D space between point pair X and X_a is given by,

$$\begin{bmatrix} x_a \\ y_a \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \quad (1)$$

B. Similarity Metric

The measure of similarity between images or regions is important in image registration along with the selection of the transformation function [1]. Higher similarity between images after registration means better alignment. In this section, we present the two metrics used in this work, sum of squared differences (SSD) and mutual information (MI).

1) SSD: The SSD metric computes the squared differences between intensity values for corresponding pixels. This is a linear relationship between intensities in the images to be compared and its optimal value is 0 (images are identical). Equation 2 (a), where A and B stand for the images and i iterates over the I pixels in the images, equation (2) shows how to compute this metric.

$$SSD(A,B) = \frac{1}{I}\sum_{i=1}^{N}(A_i - B_i)^2 \quad (2)$$

2) MI: MI provides a measure of probabilistic mutual dependence between two intensity distributions. MI allows accounting for nonlinear differences in intensity (a feature often useful in multimodality registration) and is defined as:

$$MI(A<B) = H(A) - H(B/A) = H(A) + H(B) - H(A,B) \quad (2a)$$

where A and B are the images to be compared

$$H(X,Y) = -\sum_{x,y=0}^{N} P(x,)\cdot \log_2(p_{x,y}) \quad (2b)$$

$$H(X) = -\sum_{i=0}^{N} p \cdot \log_2 p(x) \quad (2c)$$

where (2a), (2b), (2c) represents the joint the joint and individual entropies, respectively, of random variables X, Y associated to the images to be compared. Here, N stands for the number of intensity levels and p_x, (p_{xy}) is the probability value of x (x,y) in the (joint) probability distribution of variable X (X and Y). As is usual in a registration framework, parameters are recovered by optimizing a similarity measure (Figure 1). First, as part of the objective function which is to be optimized during the registration process. Second, as a measure on the success of this process. Regarding the optimizer method, gradient descent optimizer is used and in terms of interpolation, linear interpolation has been used in all cases as it provided the right trade-off between accuracy and execution time. Fig.1 shows the general framework for image registration.

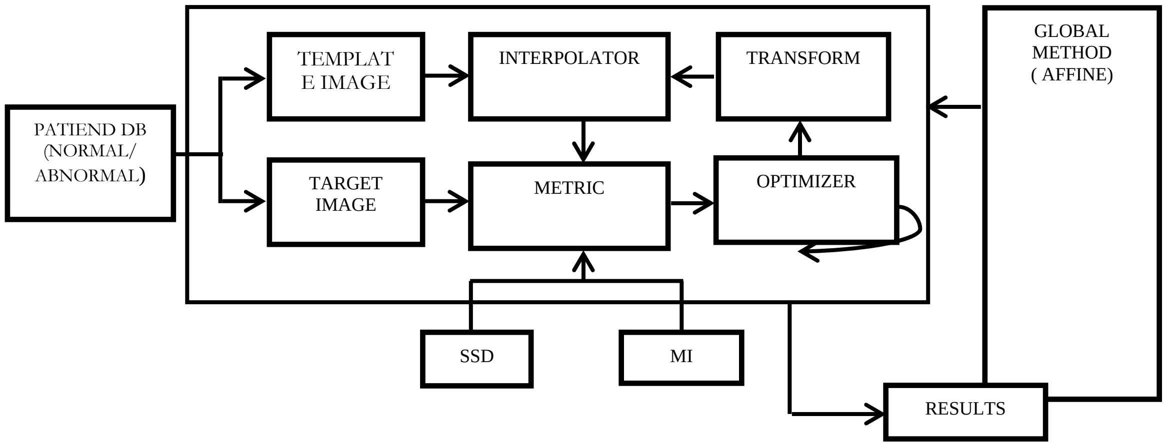

Figure 1. General image registration framework used

Medical Image Retrieval

The medical image retrieval is carried by DFT, DCT, DWT, CWT and RCWF. Each of the transforms were experimented separately. Then comparison of retrieval performance is evaluated.

A. Discrete Fourier Transform

The DFT transform converts time or space based data into frequency - based data. They estimate component frequencies in data from a discrete set of value sampled at fixed rate. The sequence of N spatial complex coefficients x_0, x_1,..x_{N-1} is transformed in to sequence of N frequency complex coefficients x(0) ,x(1) ,……,x(N-1) by the DFT and is given in the Eq (3)

$$X(K) = \sum_{N=0}^{N-1} x(n) \exp \frac{(-j2\pi nk)}{N} \tag{3}$$

where n=0, N-1

B. Discrete Cosine Transform

A Discrete Cosine Transform (DCT) expresses a sequence of finite number of data points in terms of a sum of cosine functions which were oscillating at different frequencies. They are conceptually similar to DFT. This transform is exactly equivalent (up to an overall scale factor of 2) to a DFT of 4N real inputs of even symmetry where the even – indexed elements are zero. That is, it is half of the DFT of the 4N inputs yin=0, $y_{2N+1}=x_n$ for $0<=n< N$, and $y_{4N+1}=y_n$, for $0<n<2N$. Equation (4) defines DCT.

$$Xk = \sum_{n=0}^{N-1} x_n \cdot \cos\left[\frac{\pi}{N}\left(n+\frac{1}{2}\right)k\right], \ k = 0, ..., N\text{-}1 \tag{4}$$

C. Discrete Wavelet Transform

The discrete wavelet considered here is Haar wavelet (Figure 2). The Discrete Wavelet Transform (DWT) is used as a feature extraction and/or classification tool, because of its ability to localize structures with good resolution in a computationally effective manner. The results achieved using them are unique and edge details are quantified efficiently by few coefficients. These coefficients may be used as feature themselves, or features can be computed from wavelet domain. The wavelet transform offers solutions to all the problems associated with other basis function.. It offers a multi resolution representation (decompose the image using various scale- frequency resolution). The equation (5) (5a) (5b) shows the haar scaling function while (6) and (7) gives the detail for calculating the scaling function and wavelet function. The equation (8) and (9) gives the detail for calculating sub signal and their details. The above transformation is depicted in Fig.2.

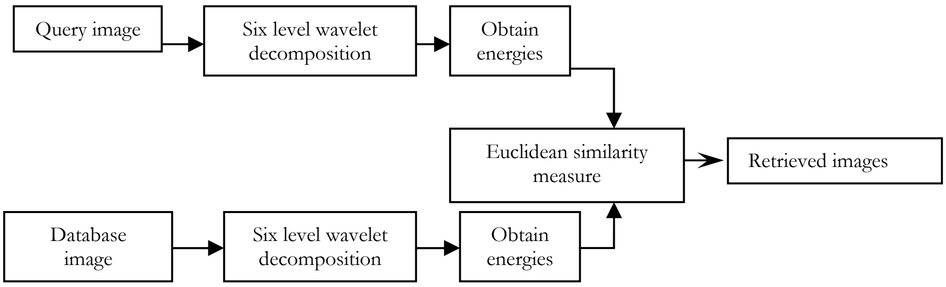

Figure 2. Haar wavelet based image retrieval

$$h_1(\Phi) = [h_1\ \Phi(0), h_1\ \Phi(1\text{-}0) = h_1\ \Phi(1) = [1/\sqrt{2}, 1/\sqrt{2}]] \quad (5)$$

Then,

$$h_\Phi(0) = (-1)^0\ [h_\Phi(1\text{-}0)] = h_\Phi(1) = 1/\sqrt{2} \quad (5a)$$

$$h_\Phi(1) = (-1)^1\ [h_\Phi(1\text{-}1)] = -h_\Phi(1) = 1/\sqrt{2} \quad (5b)$$

Wavelet function ψ(x) can be described as,

$$\psi(x) = \begin{cases} 1 & 0 \le x \le 1/2 \\ 1 & 1/2 < x < 1 \\ 0 & \text{elsewere} \end{cases} \quad (6)$$

Scaling function Φ(x) can be described as

$$\Phi(x) = \begin{cases} 1 & 0 \le x \le 1 \\ 0 & \text{elsewhere} \end{cases} \quad (7)$$

Haar transforms decomposes signal in to an average (approximation) component and a detail (fluctuation) component. A signal with 2n sample values, the first average sub signal a1 (a1, a2, ….., an/2) for a signal length of N is given as follows:

$$a = \frac{y_{2n-1} - y_{2n}}{\sqrt{2}}, n = 1, 2, ... \quad (8)$$

And the first detail sub signal d = ($d_\downarrow 1\ d_\downarrow 2\ d_\downarrow 3$ ... ... $d_\downarrow(N/2)$)
is given as

$$d_n = \frac{y_{2n-1} - y_{2n}}{\sqrt{2}}, n = 1, 2, ... \quad (9)$$

D. Complex Wavelet Transform

Real DWT has poor directional selectivity and it lack with shift invariance. It is found that both the above problems can be solved effectively using complex wavelet transform (CWT) by introducing limited redundancy in the transform. They provide true directional selectivity with six band pass sub images of complex coefficients which are strongly oriented at 15 °, 45°, 75°. The image texture is represented using the quantized DT- CWT coefficients [5]. Since the DT-CWT coefficients are complex valued, only magnitude quantization of DT-CWT coefficients is performed and phase information is coded separately.

$$f(x) = \sum_{l\in Z} s_{j0,l}\Phi_{j0},l(x) + \sum_{j\geq j_0}\sum_{l\in Z} c_{j,l}\psi_{j,l}(x) \tag{10}$$

where $s_{j0,l}$ is scaling coefficients and $c_{j,l}$ are complex wavelet coefficients with Φ_{j0} and $\psi_{j,l}$ complex.

$$\Phi_{j0} = \Phi^{i}_{j_{0,l}} + \sqrt{-1\Phi^{i}_{j_{0,l}}}, \quad \Phi_{j0,l} = \psi^{i}_{j0,l} + \sqrt{-1\psi^{i}_{j0,l}} \tag{11}$$

The real and imaginary parts of the DT - CWT are computed using separate filter bank structures with wavelet filters h_0 h_1 and g_0 g_1 for the imaginary part. Figure 3 shows the flow of 1-D dual tree complex wavelet transforms and is implemented using two filter banks in parallel operating on the same data. In 2-D, the CWT decomposes an image using dilation and translations of a complex scaling function and six complex wavelet functions. Impulse response of these six wavelets associated with 2-D complex wavelet transform is as a gray-scale image. These six wavelet sub bands of the 2-D DT-CWT were strongly oriented by direction and it captures image information in that direction. The complex wavelet transform discriminate between features at positive and negative frequencies. Hence, there are six sub bands capturing features along lines at angles of 2D – DTCWT. They are strongly oriented at θ = {+15°, +45°, +75°, -15°, -45°, -75°}.

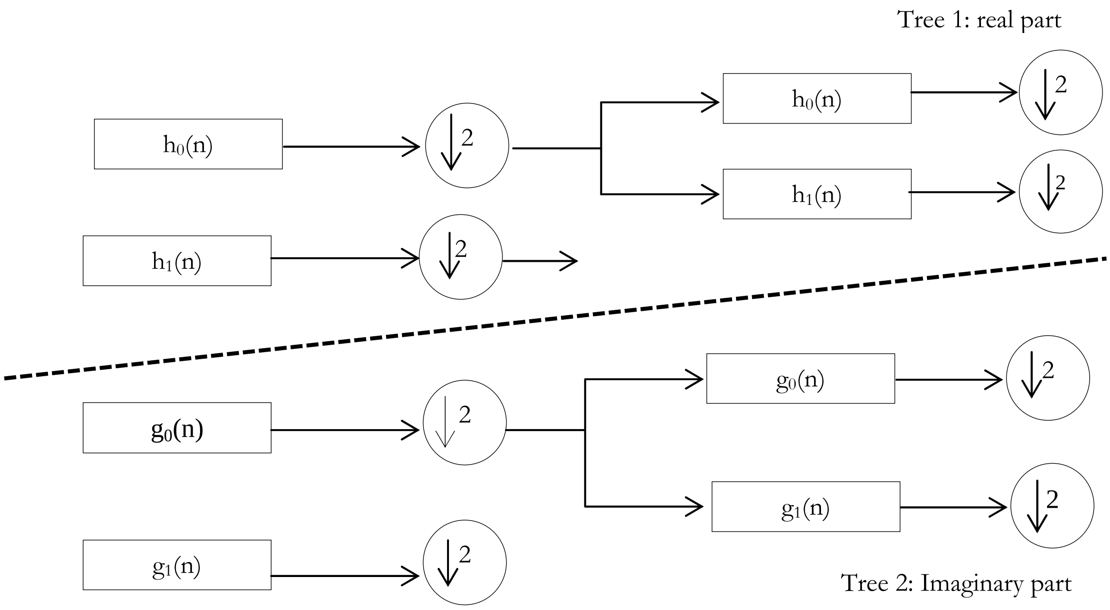

Figure 3. The 1-D dual tree complex wavelet transforms

E. 2-D Rotated Complex wavelet filters

Edge information is very important in characterizing texture properties [5]. For designing directional 2-D RCWF, first we obtain the directional 2-D complex wavelet filters and then those filters are obtained by using equations (13) - (20) rotated by 45º.

If

$\psi_1(g)(x) = H\{ \psi_1(h)(x)\ \psi_1(H)(y)\}$ (12)

$\Phi_1(x,y) = \Phi_h(x)\ \Phi_h(y)$ (13)

$\Phi_2(x,y) = \Phi_g(x)\ \Phi_g(y)$ (14)

$\psi_{1,1}(x,y) = \psi^{+15°}(x,y) = \Phi_h(x)\ \Phi_h(y)$ (15)

$\psi_{2,1}(x,y) = \psi^{-15°}(x,y) = \Phi_g x)\ \Phi_g y)$ (16)

$\psi_{1,2}(x,y) = \psi^{+75°}(x,y) = \Phi_h(x)\ \Phi_h(y)$ (17)

$\psi_{2,2}(x,y) = \psi^{-75°}(x,y) = \Phi_g(x)\ \Phi_g(y)$ (18)

$\psi_{1,3}(x,y) = \psi^{+45°}(x,y) = \Phi_h(x)\ \Phi_h(y)$ (19)
$\psi_{2,3}(x,y) = \psi^{-45°}(x,y) = \Phi_g(x)\ \Phi_g(y)$ (20)

Then the six wavelets defined by
$\psi_1(i)(x,y) = 1/\sqrt{2}\ (\psi_1(1,i)(x,y) + \psi_1(2,i)(x,y))$ (21)
$\psi_1(i+3)(x,y) = 1/\sqrt{2}\ (\psi_1(1,i)(x,y) - \psi_1(2,i)(x,y))$ (22)
Wavelet transform based on these six wavelets can be implemented by taking sum and difference is preceded by two separable 2-D DWTs. The resulting directional wavelet transform is two – times redundant. The inverse is carried by taking sum and difference, and then dividing by 2. The six sub bands of the 2-D DT-CWT gives information strongly oriented at {±15º, ±45º, ±75º}. The wavelet functions were calculated by using equation (21)-(22). Hence the decomposition is performed along the new direction of CWT. The size of the filter is (2N-1) × (2N-1), where N is the length of 1-D filter. The decomposition of input image with 2-D RCWF can be performed by filtering a given image f (x, y) with 2-D RCWFs followed by 2-D down sampling operations $h_A h_{1,1} h_{1,2} h_{1,3}$ $g_A g_{1,1} g_{1,2} g_{1,3}$ were rotated by 45º and obtained by using above equations. They correspond to $\Phi_1\Psi_{1,1}$ $\Psi_{1,2}$ $\Psi_{1,3}$ $\Phi_2\Psi_{2,1}$ $\Psi_{2,2}$ $\Psi_{2,3}$ respectively. The rotated complex wavelets are strongly oriented at {-30º, 0º, 30º, 60º, 90º, 120º} directions. This characteristic of RCWF provides complementary information to the CWT filter set in extracting texture features in 12 different directions.

Medical Image Based Registration and Retrieval

The affine based medical image registration is carried for registration of medical images. Then, the experiment is processed as registration based retrieval for medical images. Same processing steps were carried for registration and retrieval. The experimental setup and results shows the need for registration based retrieval. The results were clearly discussed in the later section. The, results helps to categorize as two sections. Retrieval results before registration and retrieval results after registration.

Results

After performing the registration and retrieval separately, the registered image using affine based registration is applied for retrieval. This section helps in finding the best retrieval technique to be applied for medical image based registration and retrieval.

Implementation Details for Registration

The Registration methods have been implemented using the MATLAB. On one hand, the two images to be aligned so that the main anatomical structures match. On the other hand structures also carry important information that could be taken into account in order to recover a more local; deformation. Images were selected from a database of MRI images without movement artifacts and abnormalities such as operation defects. The visual observation is carried by using an observer study carried by 11 observers with a different degree of expertise in both medical image analysis and radiology: one export radiologists, one trainee radiologists, and five computer vision experts with 5 year experience (2), five to ten year experience (1) , and less than five years' experience (2) in medical image analysis.

Implementation details for retrieval

An Intel core 2 Duo computer has been used for conducting the experiments. The developed user interface components are database of medical images serving as front end. MATLAB 7.10.0-image processing toolbox- workspace was used as feature database for storage as backend and for image processing work other MATLAB 7.10.0 utilities were used for mathematical equations. Math type tool was also used for writing document. Initially, MATLAB 7.10.0 workspace database with 1000 medical images were used for testing the proposed CBMIR system. No toolkit has been used, no browsers were needed, an easy interpretation and representation is possible only with limited number of images. But this is not the restriction in this work. This can be rectified by the experimental setup by creating databases (DB1) for head images in the database alone. Database (DB2) for thorax images alone. Similarly Database (DB3) for abdomen images alone. Database (DB4) for pelvis and perineum images alone. Database (DB5) for limbs images alone each with 790 images. This can be implemented at various levels i.e. level 1 (DB1), level 2 (DB2), level 3 (DB3), level 4 (DB4), level 5 (DB5). The point to be cleared here is, this is small scale level carried work carried for registration and retrieval of medical images.

Retrieval Strategies

For retrieval efficiency, traditional measures namely Precision and Recall were computed with 500 medical images as test samples. Standard formulas have been computed for determining the Precision and Recall measures. For the analytical notion of performance along with the subjective evaluation, we used the traditional precision-recall value (PR) performance metrics measured under relevant (and unbiased) conditions. The precision and recall values were given in Eq(23) and Eq(24).

$$R= RR/TR \tag{23}$$

$$P= RR/N \tag{24}$$

Where RR is the number of relevant items retrieved (i.e., correct matches) among total number of relevant items, TR. N is the total number of items (relevant + irrelevant) retrieved. By randomly selecting some sample query images from the MATLAB – image processing tool box- Workspace database, the system was tested and the results are shown. The query processing and feature extraction with distance classification are the two main processes in retrieval of images. The Euclidean distance is used for distance classification and energy as feature extraction technique in the retrieval of medical images. The Euclidean distance metrics and energy as the measure is followed as second step in the retrieval of medical images. The direct Euclidean distance calculation between a database image p and query image q is given below. By using Eq (25) Euclidean distance metric is made possible. Where i=1 ton.

$$\text{Euclidean distance} = \sqrt{\textstyle\sum} (v_{pi}-v_{qi})^2 \tag{25}$$

It is a gray-scale image texture measure for homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture. Here p(x, y) is the gray-level value at the coordinate (x, y). Energy measure can be calculated from Eq (26)

$$\text{Energy } E = \textstyle\sum_X \sum_Y P(x, y)^2 \tag{26}$$

Registration based Retrieval Strategies

To our knowledge this is the first attempt to quantitatively combine registration and retrieval for medical images. Specifically taking in to account the quantitative and evaluation criteria used in this work: metric comparison, an observer study, running time analysis were evaluated for a subset of images before and after registration. For registration based retrieval efficiency, precision and recall values were calculated. Subsequently, registration results are presented, providing details on the data and experiments (Figures 4-6).

Quantitative analysis for registration based retrieval for medical images. The error rate and retrieval efficiency can be calculated from below equations for effective performance analysis.

$$\text{Error rate} = \frac{\text{Number of non relevant images retrived}}{\text{Total number of images retrieved}} \tag{23}$$

$$\begin{aligned}
&\text{if number of retrival} > \text{number of relevant}\\
&\text{Retrival efficacy} = \frac{\text{Number of relevant images retrived}}{\text{Total number of images retrieved}}\\
&\text{else}\\
&\text{Retrival efficacy} = \frac{\text{Number of relevant images retrived}}{\text{Total number of relevant...}}
\end{aligned} \tag{24}$$

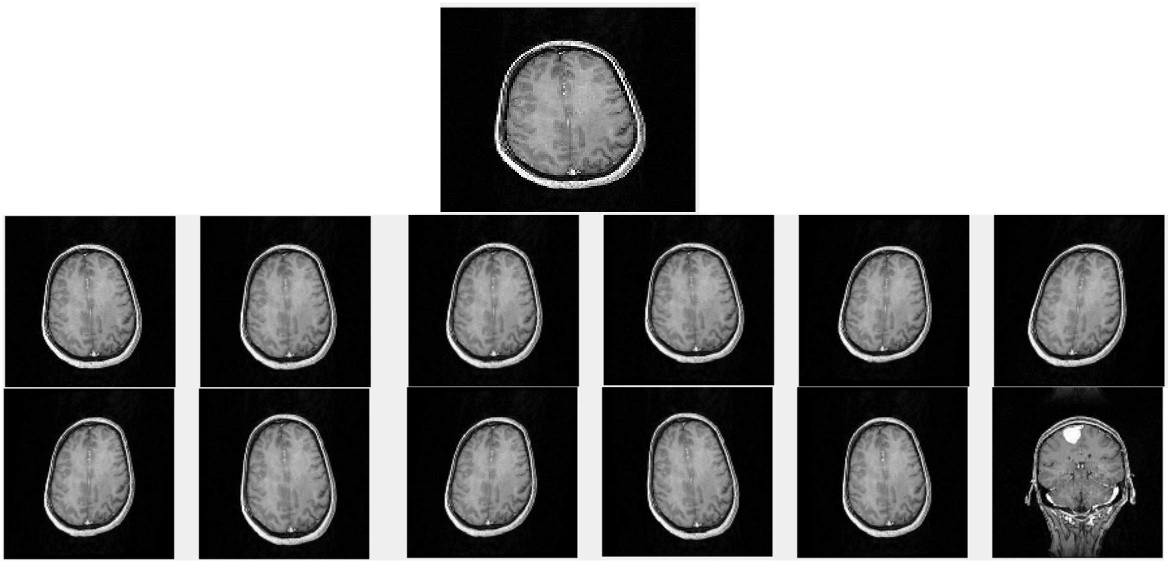

Figure 4. DWT based image retrieval without registration

Figure 5. Top left is the test image and next is the reference image to be registered and top right is the affine based registered image

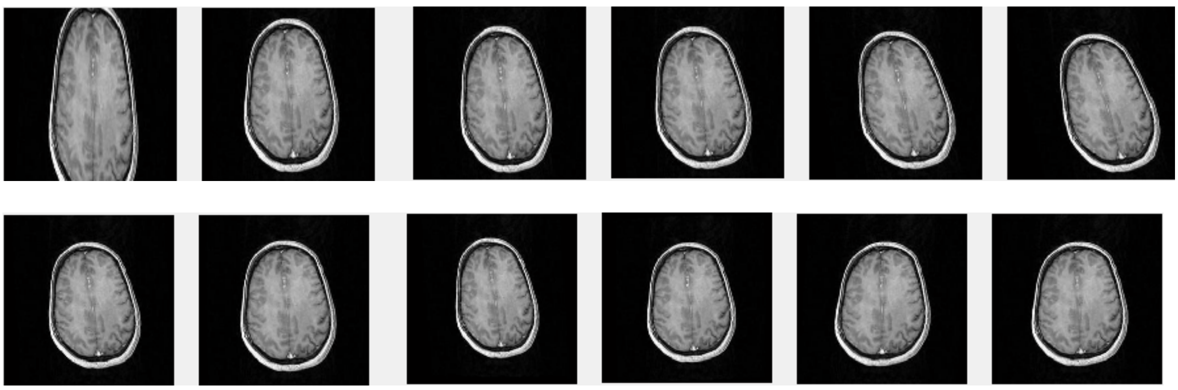

Figure 6. CWT based image retrieval with registration

Table 1. Detail of retrieval performance without registration from retrieved images

Transforms	Relevant images	Irrelevant images	Actual images
DFT	5	6	1
DCT	3	7	2
DWT	10	1	1
RCWF	7	3	2
CWT	9	2	1

DFT = Discrete Fourier transform; DCT = Discrete cosine transform;
DWT = Discrete wavelet transform; RCWF = Rotated complex wavelet filters; CWT = Complex wavelet transform.

Table 2. Detail of retrieval performance with registration from retrieved images

Transforms	Relevant images	Irrelevant images	Actual images
DFT	11	NIL	1
DCT	10	1	1
DWT	3	7	1
RCWF	4	7	1
CWT	11	NIL	1

DFT = Discrete Fourier transform; DCT = Discrete cosine transform;
DWT = Discrete wavelet transform; RCWF = Rotated complex wavelet filters; CWT = Complex wavelet transform.

Table 3. Evaluation of Retrieval performance without registration

Transforms	Precision	Accuracy	Efficiency	Error rate
DFT	41	16	42	0.5
DCT	25	10	25	0.58
DWT	83	33	83	0.08
RCWF	58	23	58	0.25
CWT	75	30	75	0.16

DFT = Discrete Fourier transform; DCT = Discrete cosine transform;
DWT = Discrete wavelet transform; RCWF = Rotated complex wavelet filters; CWT = Complex wavelet transform.

Table 4. Evaluation of Retrieval performance with registration

Transforms	Precision	Accuracy	Efficiency	Error rate
DFT	90	36	100	NIL
DCT	83	33	83	0.08
DWT	25	10	25	0,58
RCWF	33	13	33	0.58
CWT	91	36	100	NIL

DFT = Discrete Fourier transform; DCT = Discrete cosine transform;
DWT = Discrete wavelet transform; RCWF = Rotated complex wavelet filters; CWT = Complex wavelet transform.

Table 5. Registration performance before registration

Parameters	Test image	Reference image
Mean	24.9159	47.32
Variance	2980.61	4708.32
SSD	125.204	
MI	0.8767	

SSD =Sum of squared difference ; MI = Mutual information

Table 6. Registration performance after registration

Parameters	Affine based registration
Mean	28.3869
Variance	3.2318
SSD	126.65
MI	1.0138

SSD = sum of squared difference ; MI = Mutual information

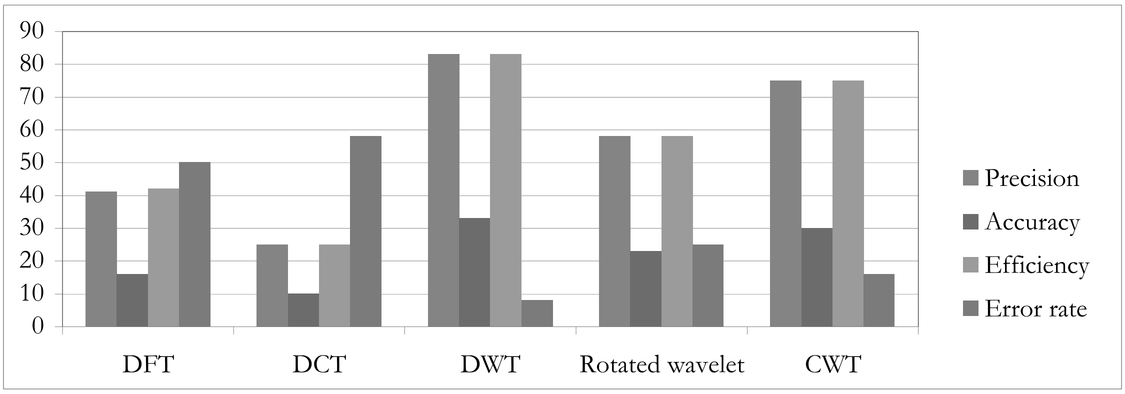

Figure 7. Overall performance of transforms before retrieval and DFT = Discrete Fourier transform; DCT = Discrete cosine transform;DWT = Discrete wavelet transform; RCWF = Rotated complex wavelet filters; CWT = Complex wavelet transform.

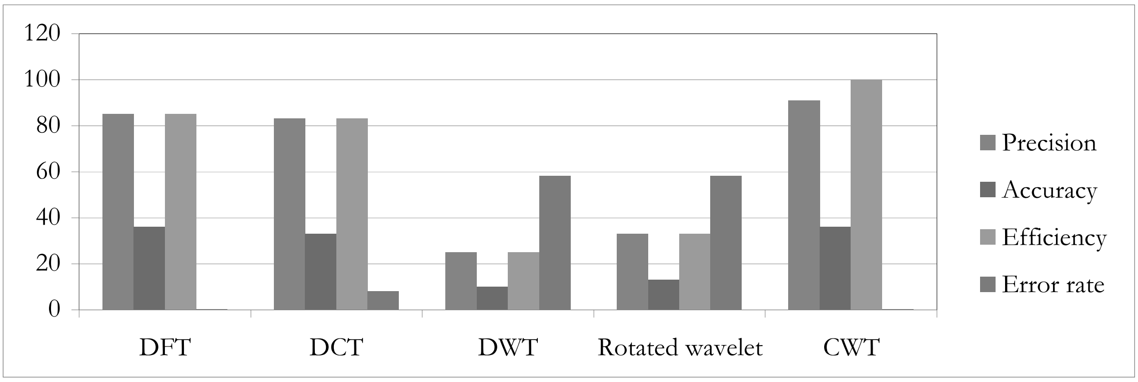

Figure 8. Overall performances of transforms after retrieval and DFT = Discrete Fourier transform; DCT = Discrete cosine transform; DWT = Discrete wavelet transform; RCWF = Rotated complex wavelet filters; CWT = Complex wavelet transform.

Discussion

From our experiment it is found that for registration of medical images the similarity metric value SSD and MI found to be higher i.e. before and after registration which means higher metric value then higher similarity i.e. SSD with 126.65 and MI of 1.0138 after registration which is greater than before registration. The metric for quantitative analysis and for subjective analysis observer study is carried with experts. Form their view also visual similarity found to be high confirming the affine based registration to be with good registration results and is shown in fig. 5 and in table .5. The reason for affine base registration for medical images is carried to help radiologists and physicians to transform the image in various orientations for clear and subjective view by selecting the control point, for effective clinical diagnosis and treatment. This also reduces the time for decision making in diagnosis and treatment. This is for retrieval; it is found that, DWT performs well in retrieval with 83% precision, 33% accuracy, 83% efficiency and 0.08% of lesser error rate which is clearly shown in fig. 7 and fig.8. Overall performance of transforms before retrieval ia also shown in graphical representation where y axis represents the range from (0-100) of the values for precision, recall, efficiency and error rate. Details of retrieved images and evaluation were shown in table 1, 2, 3 and 4. This retrieval technique using transforms helps in reducing the searching time and retrieving the images similar to the query image which found to be more similar. This also helps in diagnosis, clinical treatment and quicker remedy in surgical planning. For registration based retrieval by applying the affine based transformation image with the CWT transform for retrieval found to be better with 91% precision, 36% accuracy, 100% efficiency and without any error rate.

Hence registration based retrieval found to be best in all aspects from their retrieval evaluation. The reason behind this is while performing registration there will be a slight spatial alignment change in the image. DWT which performs well in retrieval without registration performs poor in retrieval with registration. Because DWT has poor directional selectivity and lack in shift invariance. The reason for CWT to perform well in affine based registration with retrieval is they provide more directional selectivity which is already explained briefly and results are shown in fig. 6 and in table 6. They were strongly oriented in 15°, 45°, 75° this is more enough. Thus this discussion helps in classification of results proving that registration based retrieval performs well in medical images.

Conclusions

We have quantitatively evaluated using state-of-the art recognition. Over all, we obtained significant results in the retrieval with before and after registration. DWT performs well in retrieval. But affine registration with CWT obtained the best results from the numeric as well as the subjective point of view for registration based retrieval. This retrieval flow performs well in medical showing high performance results. Experimental results also confirm that the results of affine with CWT performs well in registration based retrieval in terms of precision, accuracy and in terms of lesser error rate, searching time and enhancing the retrieval for effective diagnosis and clinical evaluation. This reduces the searching time and higher retrieval rate for searching from the past and relevant database. The point to be noted from this work is this helps in choosing the best method for effective retrieval and registration for medical images. Because medical imaging based retrieval is a vast area and with many more complexities as previously described, this helps in choosing the combination for registration methods and retrieval measures.

List of abbreviations

Content based image retrieval (CBIR)
Content based medical image retrieval (CBMIR)
Discrete Fourier transform (DFT)
Discrete cosine transform (DCT)
Discrete wavelet transform (DWT)
Complex wavelet transform (CWT)
Rotated complex wavelet transform filter (RCWF)
Provide the full list of abbreviations used in the manuscript

Conflict of Interest

The authors declare that they have no conflict of interest.

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